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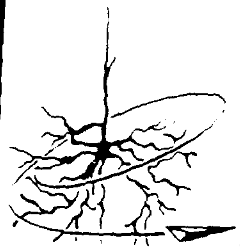

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This research was sponsored by the
Defence Advanced Research Projects Agency
ARPA Order No.: 3700
Contract No.: MDA 903-80-C-0291
Monitored by Lt. Col Jacobsen, Materials Science Office

Final Technical Report

APPLICATION OF ADAPTIVE LEARNING NETWORK MODELING TO SINGLE-PARTICLE EROSION TEST DATA

Contract No. MDA903-80-C-0291

February 1982

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REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER

2. GOVT ACCESSION NO.

3. RECIPIENT'S CATALOG NUMBER

4. TITLE (and Subtitle)

Application of Adaptive Learning Network Modeling to Single-Particle Erosion Test Data

5. TYPE OF REPORT & PERIOD COVERED

Final Technical Report
Feb. 1980 - Feb. 1982

6. PERFORMING ORG. REPORT NUMBER

ADI 561

7. AUTHOR(s)

Joseph N. Craig and Francis J. Cook

8. CONTRACT OR GRANT NUMBER(s)

MDA903-80-C-0291

9. PERFORMING ORGANIZATION NAME AND ADDRESS

Adaptronics, Inc.
1750 Old Meadow Road
McLean, VA 22102

10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS

11. CONTROLLING OFFICE NAME AND ADDRESS

Defense Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, VA 22209

12. REPORT DATE

February 1982

13. NUMBER OF PAGES

53

14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)

Same

15. SECURITY CLASS. (of this report)

Unclassified

15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

[redacted]

APPROVED FOR PUBLIC RELEASE
DISTRIBUTION UNLIMITED

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Erosion Resistance, Carbon-Carbon Composites, Adaptive Learning Networks

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The methodology of Adaptive Learning Network Training has been used to model mass loss ratios resulting from single-particle impacts on carbon-carbon composite materials. The resulting ALN models identify material bulk density, graphitization temperature, dynamic hardness (A), and the stiffness exponent (N) as the parameters that most affect the erosion resistance of Series 300 and Series 400 materials. The development of more detailed models was made difficult by the limited variety in the experimental data base.

FOREWORD

This final technical report describes work performed by Adaptronics, Inc. under Contract No. MDA903-80-C-0291 during the period March 1980 to October 1981.

Dr. Robert D. Craig, AFWAL/MLBE, served as Project Engineer for this work. The authors thank him and Drs. William B. Kessler of AFML and Michael J. Buckley of DARPA for their interest, encouragement, and support.

Dr. Joseph N. Craig served as Principal Investigator for Adaptronics. Contributions by Ms. Paul S. Bershader, Messrs. Andrew R. Barron; John F. Elder, IV; Dodd C. Deifibaugh; and Ms. Jennifer Lynch are appreciated.

ABSTRACT

The methodology of Adaptive Learning Network Training has been used to model mass loss ratios resulting from single particle impacts on carbon-carbon composite materials. The resulting ALN models identify material bulk density, graphitization temperature, dynamic hardness (A), and the stiffness exponent (N) as the parameters that most affect the erosion resistance of Series 300 and Series 400 materials. The development of more detailed models was made difficult by the limited variety in the experimental data base.

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1. INTRODUCTION

The development of erosion-resistant carbon-carbon nosetip materials is a problem area of current interest, particularly as water droplets and particulates in the atmosphere tend to produce nosetip erosion that affects the survivability and accuracy of re-entry vehicles. Currently, several approaches are used to advance understanding of this erosion process:

(1) analytical modeling of material properties, and

(2) experimental development and testing of materials.

There are problem areas with both approaches. The analytical models are generally quite expensive to use, and the comparison of model predictions to actual data is difficult. Analytical models are often criticized on the grounds that the input of material properties data removes the model from the category of "first principles," and the requirement that such data be input results in more, not less, experimental materials testing. Additionally, the material properties are not easily related to variables that can be controlled during the manufacturing process.

The experimental approach also has difficulties, especially the time and expense required to fabricate and test sample billets, the large number of manufacturing variables that can be altered, and the variety of tests required to determine material properties. Consideration of the many parameters that could be tested in an experimental program shows that comprehensive testing over the full ranges of all the parameters is impractical; thus experimenters must pick and choose among the subelements of the test matrices that will be populated with test data. An important limitation to such an approach is that usually only one variable at a time is altered, and therefore interactions among parameters are difficult to discover.

Additional tests are obviously necessary to couple the modeling and experimental worlds. Ideally, such tests would consider material and manufacturing parameters, and help to organize or integrate the available data for both communities.

The Adaptive Learning Network (ALN) modeling methodology is an empirical modeling methodology that can be used to aid in the study of the erosion resistance of carbon-carbon materials. The primary objective of the work reported herein has been to investigate the feasibility of using the ALN technique to organize a set of data from single-particle impact testing of carbon-carbon materials.

The principal advantage of the single-particle ballistic impact test is that it permits careful control over parameters such as impact velocity, temperature, and particle size, shape, and composition. A wide variety of materials can be tested, and the impacts on previously damaged targets can be used to study the incremental effect of a single impact during the erosion process.

The goal of single-particle-impact testing is to relate the observed cratering to the material properties, the impacting particle, and other variables such as temperature, impact velocity, and impact angle. The material properties stem from to variables controlled in the manufacturing process. These variables include material type and weave, densification techniques, graphitization processes, etc.

A well-defined model of the erosion process could, in principle, be interrogated to determine which manufacturing processes lead to acceptable (perhaps even optimum) erosion performance while meeting other constraints (such as ablation).

The work reported here is a first step in the direction of meeting these goals. Section 2 contains an overview description of the ALN modeling methodology. The data analyzed in this work are described in Section 3. The results of ALN modeling of the data are presented in Section 4. A discussion of the results, potential applications to other data, and recommendations for further research are presented in Section 5.

2. ADAPTIVE LEARNING NETWORK SYNTHESIS METHODOLOGY

2.1 INTRODUCTION

Adaptive Learning Network Synthesis is a powerful method through which data that are obtained as the result of "observing" a physical process are used to construct a model of that process. Often, the rationale for modeling a process is to detect or classify a particular occurrence in the data, to make future predictions about the process, to control the future behavior of the process, to summarize important features of the process, or, in the present case, to discover the underlying (and unknown) structure.

The classical approach in the design of detection, classification, modeling, estimation, and signal processing functions has been to determine explicitly all of the relevant characteristics (deterministic and/or statistical) of the observed process and to use those measurements and assumptions in the synthesis of the model. Often, the mathematical structure of the true process is assumed, and the design process consists of calculating the coefficients of the theoretical model equations. But, in many cases, the inputs or observables cannot be related to the output of the process in an analytical fashion. Further, the best or even an acceptable structure for the model cannot be determined a priori. Linear models are often used in these cases simply because the mathematics of more general models are falsely believed to be intractable.

When a linear model does not describe satisfactorily the particular set of data, it is desirable to implement the mathematical model as a general (usually nonlinear) function of certain input variables that we can call observables. Since the details of the relationships between the input variables and the output variable or variables (the outputs of the process) are not known, the parameters and structure of the model are not known a priori. Rather, the model has to be "trained" from a data base of representative inputs and corresponding outputs.

To achieve trainability, the Adaptive Learning Network methodology uses, as a model of the observed process, a network of similar elementary building blocks. The training process, or model synthesis, specifies the parameters of the elementary building blocks as well as their number and the interconnections between them. In this way, the structure and coefficients of the model are derived from observations of the process. The questions that must be answered to arrive at this result are:

- What should the structure of the elements of the network be?
- How should the element parameters be adjusted?
- How should the elements be interconnected and what should be their complexity (i.e., number)?

To answer these questions, suppose that the input consists of N observables, $x_1, x_2, \ldots, x_N$. Also, suppose that a given output variable is a scalar whose value may be considered as the estimate of some property of the input process. In general, y will be some nonlinear function of the x_i's:

$$y = f(x_1, x_2, \ldots, x_N) \tag{1}$$

2.2 POLYNOMIAL (MULTINOMIAL) APPROXIMATION

Under fairly general conditions, a function of N variables may be expressed in an N-dimensional series (References 1-3):

$$y = a_0 + \sum_{i=1}^{N} a_i x_i + \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij} x_i x_j + \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} a_{ijk} x_i x_j x_k + \ldots \qquad (2)$$

In the most general case, the coefficients, a_0, a_1, ..., are functions of time, but for many cases of interest, the underlying characteristics of the x's do not depend on time and, consequently, the coefficients are constants.

Two questions which arise in the use of Equation (2) are:

- What are the observables or features (x_i's)?
- How many terms in Equation (2) will provide an acceptable approximation to the desired function, f, in Equation (1)?

The answer to the first question is that those features that the analyst or designer believes could have a significant role in the application should be evaluated initially. The relevant features are selected by the learning algorithm; features that trials show to be of little or no use are discarded. The second question is answered by using a nonlinear ALN whose complexity determines the number of terms in Equation (2). The network consists of interconnected basic elements; each basic element implements a simple nonlinear function of one, two, or three inputs. The entire network is trained (by adjusting the coefficients of the basic elements and the interconnections among the basic elements) to provide an acceptable approximation to Equation (1).

The basic element of the Adaptive Learning Network is a three-input device that implements a nonlinear function of inputs x_1, x_2, and x_3:

$$\begin{aligned} y = {} & w_0 + w_1x_1 + w_2x_2 + w_3x_3 \\ & + w_4x_1x_2 + w_5x_1x_3 + w_6x_2x_3 \\ & + w_7x_1^2 + w_8x_2^2 + w_9x_3^2 \\ & + w_{10}x_1x_2x_3 + w_{11}x_1^3 + w_{12}x_2^3 + w_{13}x_3^3 \end{aligned} \tag{3}$$

To reduce computational complexity, not all elements are allowed to use three inputs. Most elements contain only two inputs x_1 and x_2:

$$\begin{aligned} y = {} & w_0 + w_1x_1 + w_2x_2 + w_4x_1x_2 \\ & + w_7x_1^2 + w_8x_2^2 + w_{11}x_1^3 + w_{12}x_2^3 \end{aligned} \tag{4}$$

Some elements contain only a single input.

2.3 NETWORKS OF THE BASIC ELEMENT

A network of two layers of basic elements can contain products up to the ninth degree. Thus, fairly complex multinomials can be built in a few network layers. To implement a fully general multinomial, the number of elements in each layer would have to grow as one adds additional layers to the network. It has been found empirically (Reference 4) that acceptable networks can be obtained without such growth; in fact, the number of elements in successive layers decreases so that only a few layers are needed in the final network.

2.4 ADAPTIVE LEARNING NETWORK TRAINING

Adaptive Learning Network training is accomplished using a training data base for which the values of the observables (independent variables) and the desired output (dependent) variable are known. Here, "independent" means independently observed; the input variables need not be statistically independent.

Figure 2.1 illustrates a hypothetical data base consisting of four independent variables and one dependent variable. We wish to construct a model of the dependent variable, y, based on observations of the independent variables, x_1, x_2, x_3, and x_4. It is assumed that M observations of $x_1, \ldots, x_4$ have been made and that the actual output of the process, y, has been determined experimentally for each observation.

$$y = F(x_1, x_2, x_3, x_4) \tag{5}$$

Five steps are involved in the training process:

(1) Optimization of the coefficients in each element of the first layer.

(2) Selection of those elements whose output is acceptable and rejection of poor performers.

(3) Iteration of (1) and (2) for successive layers of the network.

(4) Termination of network evolution before overfitting occurs.

$$Y = F(X_1, X_2, X_3, X_4)$$

Y	X_1	X_2	X_3	X_4
Y_1	x_{11}	x_{12}	x_{13}	x_{14}
Y_2	x_{21}	x_{22}	x_{23}	x_{23}
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
Y_M	x_{M1}	x_{M2}	x_{M3}	x_{M4}

FIGURE 2.1: SCHEMATIC REPRESENTATION OF EXAMPLE DATA BASE

(5) Global optimization of the coefficients of the final network (optional).

2.4.1 Partitioning of the Training Data Base

Several competing requirements must be met in the training of ALN's. The ALN model should provide a good representation of the experimental data base. The model should also provide a similarly good model for data that have not yet been observed. In other words, the model should generalize to data that have not been used in the training process. To achieve this, the ALN model should not overfit the training data. To train the network and at the same time to insure that the network does not overfit the training data, the method of Cross Validation can be used. In this case, the training data base is divided into three independent but statistically similar subsets (Reference 5).

(1) Fitting Subset (F)

(2) Selection Subset (S)

(3) Evaluation subset (E)

The fitting and selection subsets are used in the network training process. The evaluation subset is withheld from the training process and is used after ALN synthesis to evaluate the performance of the ALN. The evaluation subset serves to present new and previously unknown data to the ALN; performance on this set of data determines the extent to which the ALN is able to generalize from the training data.

The division of the data base into independent subsets may be accomplished with the Mucciardi-Gose Clustering Algorithm (Reference 6). Figure 2.2 illustrates the cluster structure typically observed in many data bases. In the multidimensional space of the independent and dependent variables, it is often seen that the data form separate groups or clusters. The clusters generally represent different states or conditions of the system. Figure 2.2 shows the structure schematically; real data clusters are considerably more complex and may form overlapping and intertwined clusters.

The division of the data base into subsets should reflect the natural structure of the data base. This is shown in Figure 2.3, where each of the clusters is randomly divided into three subsets. The subsets of the clusters are joined to form the fitting, selection, and evaluation subsets.

2.4.2 Network Training

The network structure and element coefficient determinations are based upon a numerical fit to a desired output. The fitting and selection subsets are used alternately to train each layer. First, the N possible inputs to each layer are arranged into N(N-1)/2 pairs which are used as inputs to an equal number of two-input elements. The fitting subset of the known data base is applied to establish the coefficients of each element, using a least-squares adjustment of the coefficient. Next, the selection subset is used to eliminate the poor performers: those elements whose performance is not acceptable, as measured by an error criterion. Finally, the surviving elements are examined to determine whether or not performance can be improved by using a three-input element, where two of the inputs are chosen from the best performers among the

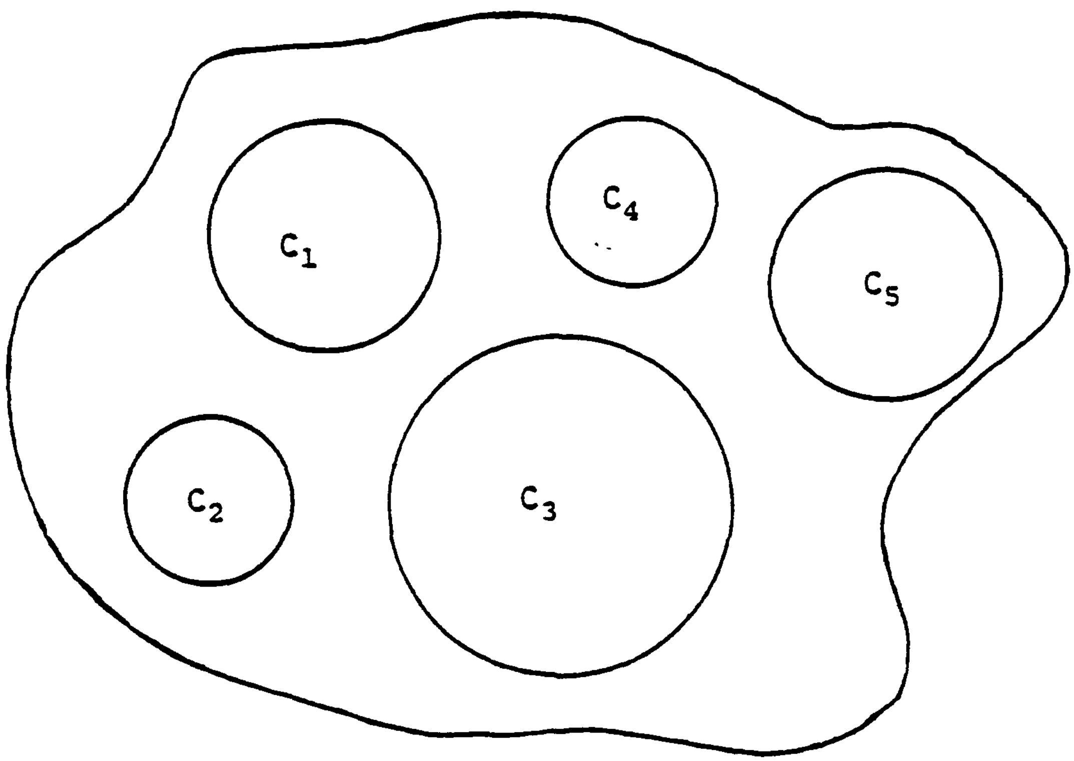
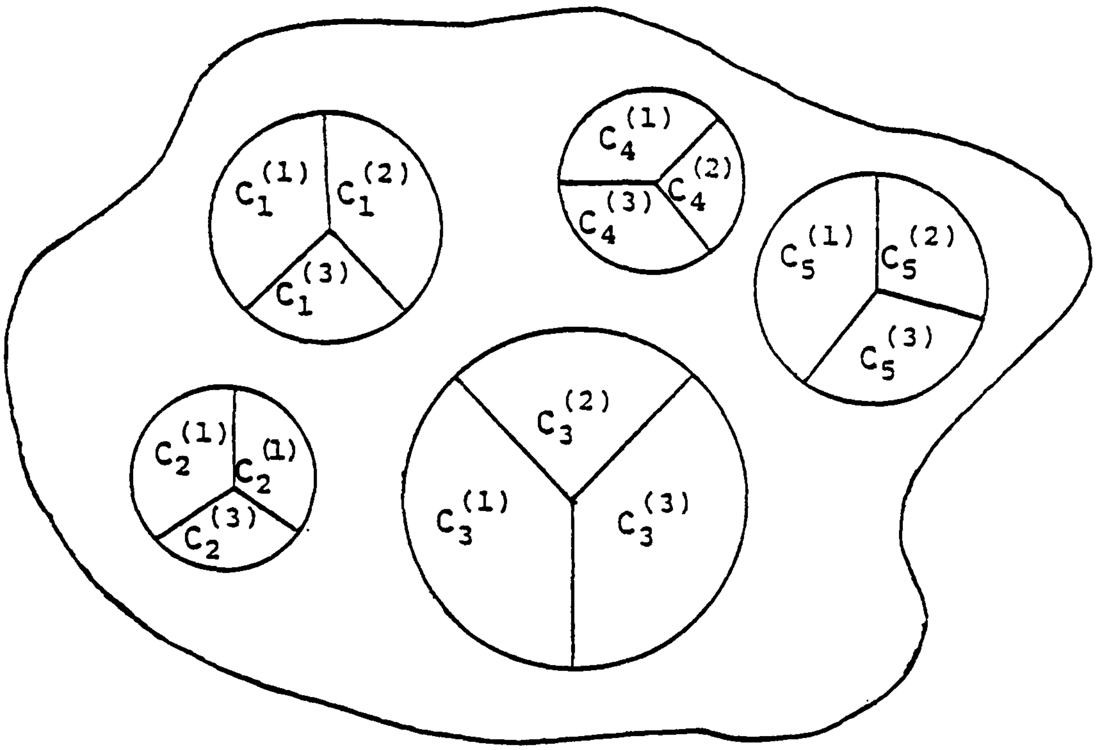


FIGURE 2.2: CLUSTERING OF DATA BASE IN DATA SAMPLE SPACE



$$F = \left\{ C_1^{(1)},\ C_2^{(1)},\ \ldots\ldots\ C_5^{(1)} \right\}$$

$$S = \left\{ C_1^{(2)},\ C_2^{(2)},\ \ldots\ldots\ C_5^{(2)} \right\}$$

$$E = \left\{ C_1^{(3)},\ C_2^{(3)},\ \ldots\ldots\ C_5^{(3)} \right\}$$

FIGURE 2.3: DIVISION OF CLUSTERS INTO F, S, AND E SUBSETS

two-input elements. Three-input elements are saved if their performance is acceptable.

In the hypothetical example, where there are four observable quantities, there are six possible elements in the first layer of the network. These are shown in Figure 2.4.

Inputs to the second layer of the network include the surviving outputs of the first layer as illustrated in Figure 2.5, as well as the original inputs to the first layer. This allows the network to include interactions among multiple observables which might be eliminated if only outputs from a previous layer lead into the next layer. Again, the fitting subset is used to adjust the coefficients of the elements; the selection set eliminates poor performers, and these input elements are examined for pairs of inputs that give good performance. Figure 2.5 shows several possible elements in the second layer of the network.

The modeling process is repeated, adding additional layers until the error rate on the selection subset reaches a minimum. The typical behavior of the error rate for the fitting and selection sets is shown in Figure 2.6. By incorporating additional layers in the network, the number of coefficients increases and the error on the fitting subset can be made arbitrarily small. At some point in the process, the error on the selection subset reaches a minimum. Beyond this, it can be seen that the network begins to take on characteristics that are exclusive to the fitting subset and different from the selection subset. Because the two subsets are statistically similar (by construction), this signifies that the network overfits the data. The addition

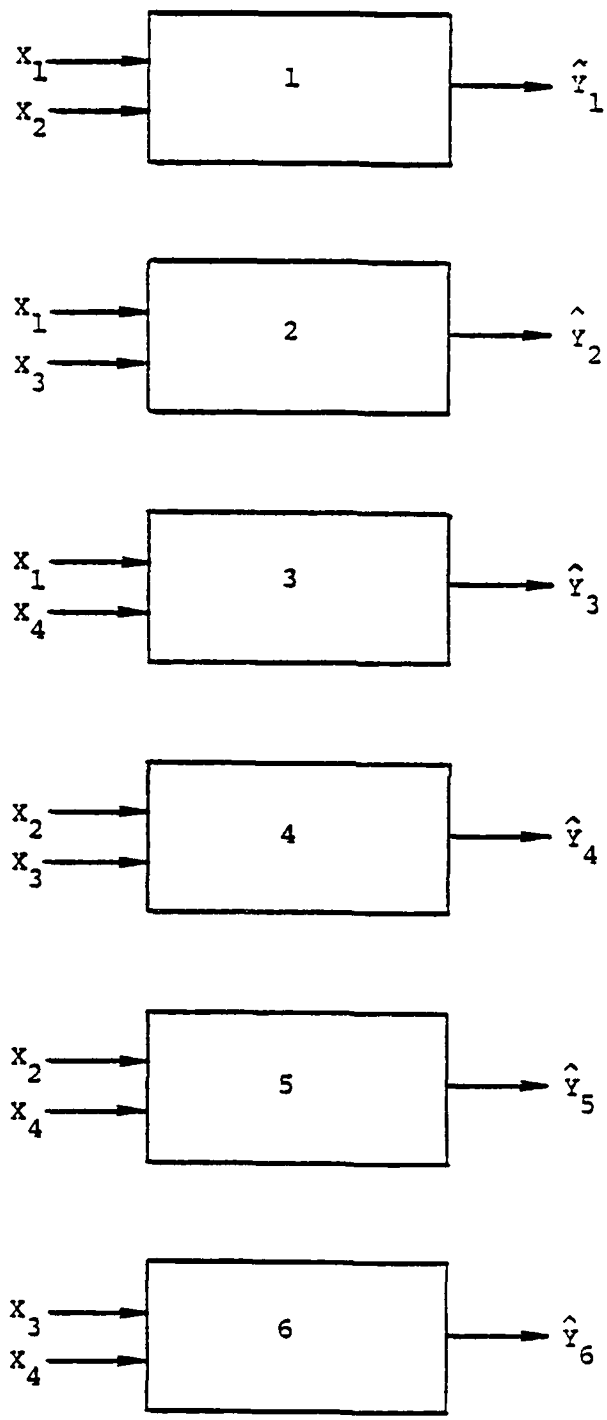


FIGURE 2.4: SIX BASIC ELEMENTS IN FIRST LAYER OF EXAMPLE NETWORK

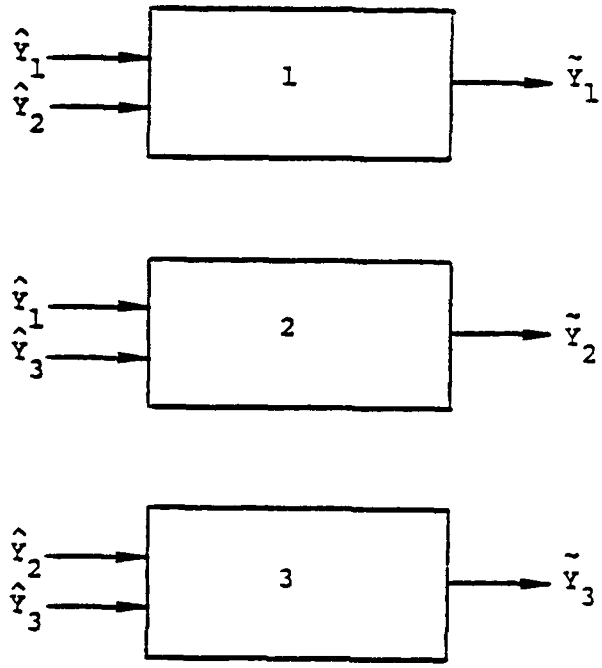
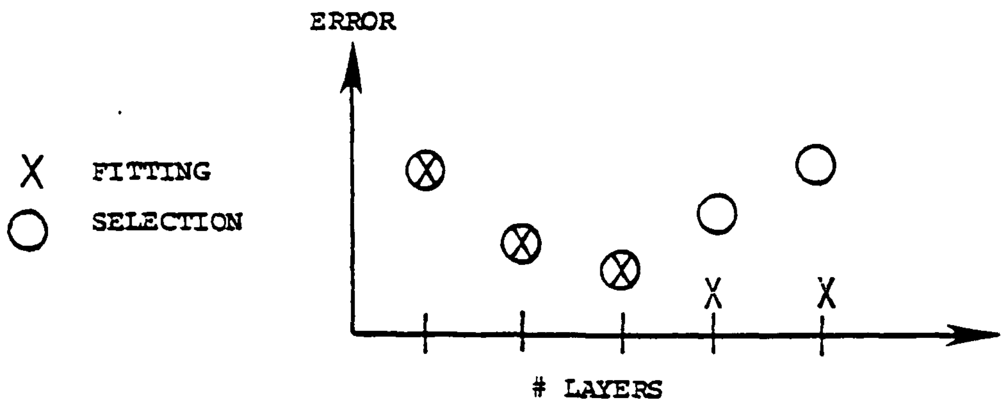


FIGURE 2.5: THREE BASIC ELEMENTS IN SECOND LAYER OF EXAMPLE NETWORK

- CROSS VALIDATION



- INFORMATION THEORETIC CRITERION

ERROR + PENALTY = MINIMUM

$$\mathrm{AIC} = -2\,\ell n\,(\text{MAXIMUM LIKELIHOOD})$$

$$+\ 2\,(\text{NUMBER OF COEFFICIENTS}) = \text{MINIMUM}$$

FIGURE 2.6: OVERFIT DETECTION

of layers is stopped where the error on the selection subset is a minimum. In Figure 2.6, it can be seen that overfitting occurs in the fourth layer of the network. Synthesis of the ALN would be terminated in this case with three layers.

When the appropriate number of layers has been found, the last layer will in general comprise a plurality of elements, each capable of producing an estimate of the dependent variable. These estimates may be weighted and summed, or the single element that produces the lowest error rate vis-a-vis the selection subset may be retained while the remaining elements not needed to feed into the surviving output are discarded. For example, in Figure 2.7, assume that Y_2 yields the best performance. In this case, the final network structure would be as is shown in Figure 2.8.

The final (optional) step in the training process is a vernier adjustment, or fine tuning, of all of the network coefficients. This step may be desirable because the coefficients of each element were adjusted in the absence of interactions among the elements. Thus, the optimum coefficient values may be different when the interactions are present. The fitting and selection subsets are also used to make the vernier adjustment. After final adjustment, the evaluation subset is used to estimate the performance of the network.

As can be seen from this discussion, the candidate independent variables that feed the final network element may be selected or rejected at several stages as the network is trained. Also, a number of basic network elements may be considered and then rejected as the final network design is reached. The ability of the training process to discard input variables allows the analyst

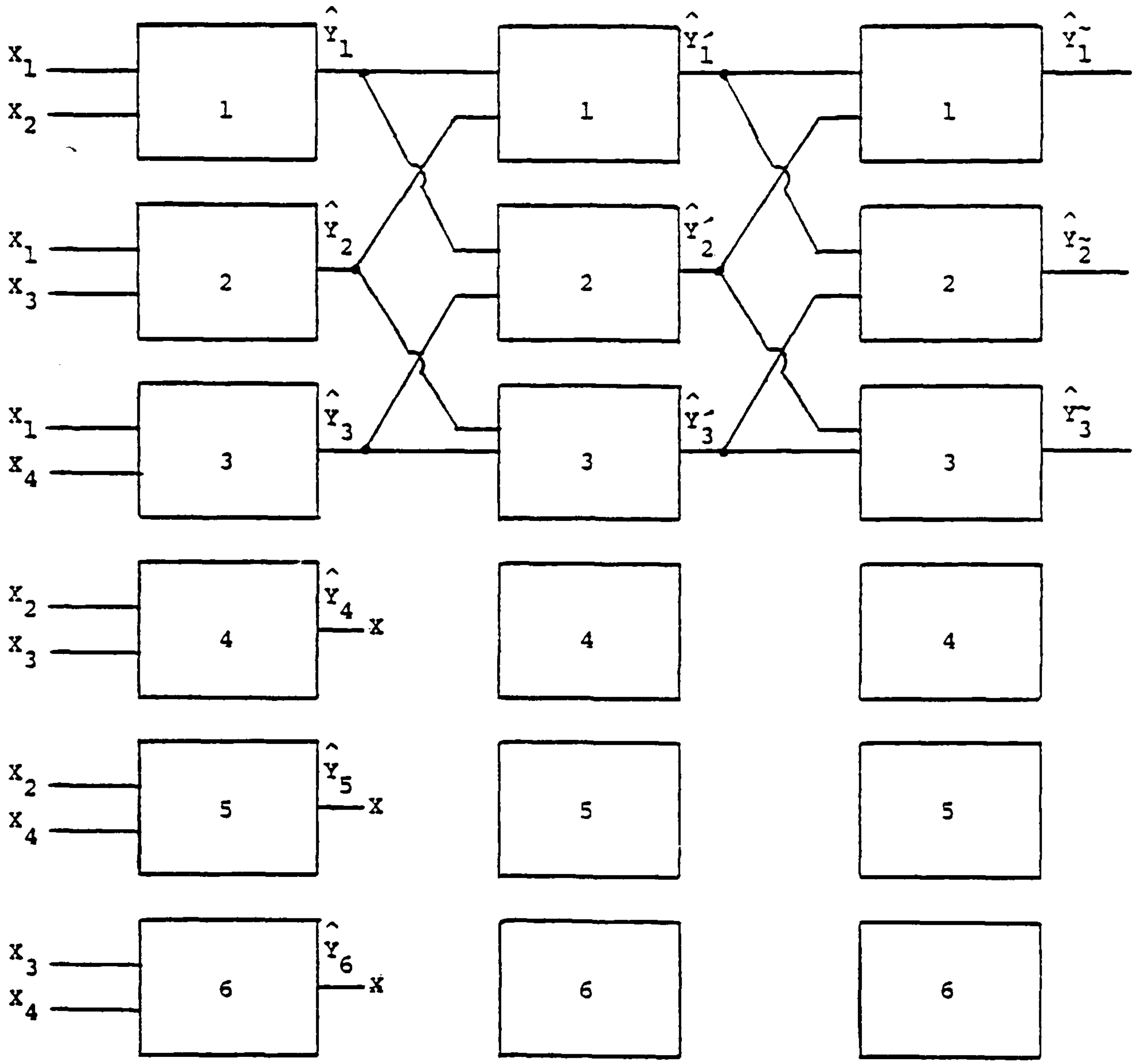


FIGURE 2.7: FULLY CONNECTED STRUCTURE OF EXAMPLE NETWORK PRIOR TO DEFINING FINAL DESIGN

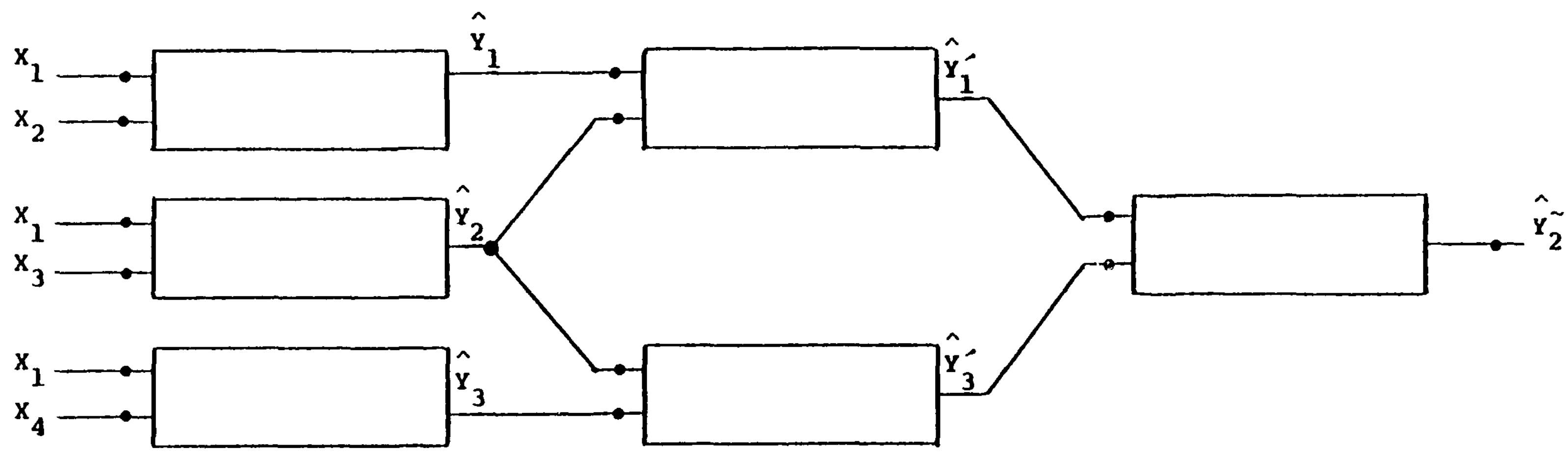


FIGURE 2.8: FINAL DESIGN OF EXAMPLE NETWORK

the freedom to propose many input variables as candidates for the network inputs. The training process determines which of these inputs are actually useful, discarding the rest. In this way, the most economical set of input variables can be used in the final network; it is not necessary to narrow down the choice to just a few candidate inputs prior to training the network.

2.5 RECENT ADVANCES IN ADAPTIVE LEARNING NETWORK SYNTHESIS

The above discussion illustrates the role of the independent fitting and selection subsets in Cross Validation training an ALN. Other techniques that make use of information theoretic criteria permit overfit detection without requiring subdivision of the training data base. One such technique makes use of an error criterion that is a modified form of Akaike's Information Criterion (AIC) (References 7 and 8). Essentially, this error criterion produces a model of the modeling process and supplies a penalty for models that contain an excessive number of parameters. The use of this error criterion obviates the need for separate fitting and selection subsets.

The modified AIC is used in Adaptronics current version of the ALN synthesis program, PNETTR IV (Reference 9). Because separate selection and fitting subsets are not required by PNETTR IV, ALN training and adjustment of coefficients can be carried out using a larger number of observations than were previously available. This is particularly useful for small data bases.

3. DATA BASE

The data that were analyzed during this project consist of single-particle impacts on carbon-carbon composite materials. Data for two basic material types (Series 300 and Series 400) were available for virgin material samples and previously damaged samples. All of the data consisted of normal-incidence impacts of a single-particle type. Testing variables included temperature, impact velocity, various material manufacturing processes, and material properties. The specific erosion damage measurements included mass loss and crater size and shape. The parameters present in the data base are given in Table 3.1.

The data were compiled from two sources. The first set of data was supplied to Adaptronics by the Air Force Materials Laboratory (AFML). A second set of data, provided by Effects Technology, Inc. (ETI) of Santa Barbara, California, added several additional observations to the available data base. The available data are described in Tables 3.2 and 3.3.

As is shown in Tables 3.2 and 3.3, the data base is limited. Additionally, complete information was not available for all data points. Thus, the results obtained in this study should not be considered to constitute broadly based models of erosion damage. Rather, these results will serve to illustrate the means by which the ALN technique can be used to organize and draw inferences from the data.

TABLE 3.1: SINGLE-PARTICLE IMPACT EROSION DATA BASE

Test Measurements

G_m - Gravimetric mass loss ratio

G_v - Volumetric mass loss ratio

Depth - Crater depth (mm)

Radius - Crater radius or width (mm)

Elong - Crater elongation (length/width)

Manufacturing Variables

Material Code - Material billet number (coded)

Weave - Type of weave used in construction

Fiber - Type of fiber

Cycles - Number of material processed heat cycles

Graph - Graphitization temperature

LastGr - Last graphitization temperature used in manufacture

CVD - Chemical vapor deposition (wt. %)

Material Properties

Bulkden - bulk density (gm/cm^3)

Openpor - open porosity of material

A - Dynamic hardness (virgin) used to define dynamic hardness

N - Stiffness exponent (virgin) used to define dynamic hardness

Shear - Dynamic shear strength at 70°C

Den - Specimen density (g/cm^3)

Test Parameters

Material State - State of material before impact (1 = origin, 2 = predamaged)

Ptype - Impacting particle type (coded)

Angle - Impact angle (degree)

MPart - Mass of impacting particle (mg.)

Vel - Impact velocity (Kft/sec)

Temp - Specimen temperature (°F) before impact

TABLE 3.2: TEST OBSERVABLES - SERIES 300

M. Code	State	GM	GV	# Observations of Depth	Radius	Elong.*
301	1	3	3	0	0	0
302	1	3	3	0	0	0
303	1	3	3	0	0	0
304	1	3	3	0	0	0
305	1	1	1	1	1	1
306	1	1	1	1	1	1
307	1	2	2	2	2	2
308	1	1	1	1	1	1
309	1	1	6	1	1	1
310	1	2	2	1	1	1
311	1	1	2	2	2	2
312	1	3	3	2	2	3
313	1	1	1	1	1	1
314	1	0	10	0	0	0
316	1	14	21	0	0	0
317	1	2	2	0	0	0
		46	64	12	12	15
306	2	3	3	1	1	3
316	2	5	0	0	0	0
		8	3	1	1	3

* Elongation is either 1.0 or not measured

TABLE 3.3: TEST OBSERVABLES - SERIES 400

				# Observations of		
M. Code	State	GM	GV	Depth	Radius	Elong.
401	1	2	2	2	2	2
403	1	10	14	14	14	14
404	1	1	8	1	1	1
405	1	2	2	1	1	2
406	1	1	2	2	2	2
407	1	2	2	2	2	2
409	1	11	13	0	0	0
410	1	2	6	0	0	0
402	1	2	2	2	2	2
408	1	2	2	2	2	2
		35	53	26	26	27
406	2	3	3	2	2	3
409	2	3	0	0	0	0
410	2	7	0	0	0	0
		13	3	2	2	3

3.1 MATERIAL PROPERTIES

The resistance of a particular material to erosion damage is obviously related to the physical properties of the material. These are, in turn, related to the manufacturing process through which the materials were created. Variations in the manufacturing process reflected in the data base are given in Tables 3.4 and 3.5.

Two basic material types are available in the data base. These are identified as Series 300 and Series 400 materials. Each is a carbon-carbon composite material consisting of a HM2000 fiber weave to which additional carbon has been added by a process known as graphitization. The Series 300 materials are based on weave type 4; Series 400 materials are based on weave type 6. The graphitization process is repeated for several cycles to add additional material. The material density increases with the number of processing cycles. Most data present in the data base were manufactured using five cycles; several observations exist for four cycles and ten cycles. As a result, the erosion damage for this data base should not depend greatly on the number of cycles used in manufacturing.

Within a given material type, the principal manufacturing variable is the temperature(s) at which the graphitization process is carried out. Two temperatures are specified in the data base: graphitization temperature and temperature of the final graphitization cycle.

Open porosity is created in the material by impregnating the material with mercury or gases prior to graphitization. The degree of porosity then depends

TABLE 3.4: SERIES 300 DATA - STATES 1 AND 2

Mat Code	Weave	Fiber	Cycles	Graph	Last Gr	CVD	# Obsv. State 1	# Obsv. State 2
301	4	2	5	2750	2750	5.32	3	
302	4	2	5	2980	2750	0.00	3	
303	4	2	5	2980	2750	0.97	3	
304	4	2	5	2980	2750	4.07	3	
305	4	2	5	2300	2300	--	1	
306	4	2	5	2300	2300	0.00	1	3
307	4	2	5	2700	2700	0.00	2	
308	4	2	5	2750	2750	4.56	1	
309	4	2	5	2700	2700	--	6	
310	4	2	4	2300	2300	0.00	2	
311	4	2	4	2450	1500	--	2	
312	4	2	5	2450	1500	--	3	
313	4	2	5	2700	2700	0.00	1	
314	4	2	5	2650	2750	1.90	10	
315	4	2	-	--	--	--	0	
316	4	2	5	2700	2700	--	23	5
317	4	2	10	2700	2700	--	2	
							66	8

TABLE 3.5: SERIES 400 DATA - STATES 1 AND 2

Mat Code	Weave	Fiber	Cycles	Graph	Last Gr	CVD	Open Por	# Obsv. State 1	# Obsv. State 2
401	6	2	5	2650	2650	0.0	-	2	
402	13	2	5	2650	2650	0.0	-	3	
403	6	2	5	2650	2650	0.0	-	14	
404	6	2	5	2700	2700	0.0	4.2	9	
405	6	2	5	2300	2300	0.0	5.5	2	
406	6	2	5	2750	2750	0.0	4.4	2	3
407	6	2	5	2750	2750	0.0	-	2	
408	6	3	5	2980	2980	0.0	6.1	2	
409	6	2	5	2700	2700	0.0	-	14	3
410	6	2	5	2700	2700	0.0	-	7	7
								57	13

on the manufacturing temperature. Porosity is also related to the strength and density of the resulting material. Open porosity is reported for only a small fraction of the available data.

Chemical vapor deposition is also reported as non-zero for a small fraction of the data base.

Material properties that result from the manufacturing process are represented by material bulk density, actual sample density, dynamic shear strength, dynamic hardness (A), and stiffness exponent (N). Values of all of these variables are not reported for all observations. The dynamic shear strength is the parameter most likely to be missing from the data base, and the hardness measurements are missing for a significant number of observations.

3.2 IMPACT TEST PARAMETERS

The primary testing variables are the impacting particle type and mass, impact angle, impact velocity, and the temperature of the sample at impact.

It is important to note that, for this data base, the range of the test variable values is quite restricted. Thus, little dependence on the impacting particle mass can be gleaned from the data. The two temperature regions in which data are available pose some problems due to the fact that, at temperatures exceeding 4000 degrees, the composite material sublimes, yielding mass loss in the absence of an impact.

Impact velocities in the range from 5 to 20 kft/sec are present in the data base. For the most part, however, the velocities are predominantly in the range of 13 to 15 kft/sec. Based on fairly simple theoretical estimates, one would expect the mass loss to vary with the kinetic energy of impact or as velocity squared. The limited data available here do not support such a determination from the data. Distributions of impact velocities are given in Figures 3.1 and 3.2.

3.3 DATA SUMMARY

Although the data are limited, there are certain variables for which there is a reasonable degree of variation present. These include the manufacturing graphitization temperatures, material density, and material hardness coefficients A and N. We can, therefore, expect that ALN models that relate erosion damage to the properties of the materials would be most easily extracted from the data base. ALN models of erosion damage as a function of impact velocity and/or temperature are less likely to represent the full physical behavior of the modeled process. Such models will, however, serve to indicate the major dependence of the erosion damage on impact velocity and/or temperature.

The two types of materials present in the data base will respond differently to erosion damage. An ALN model can be used to determine which manufacturing process or materials properties are major contributors to these differences.

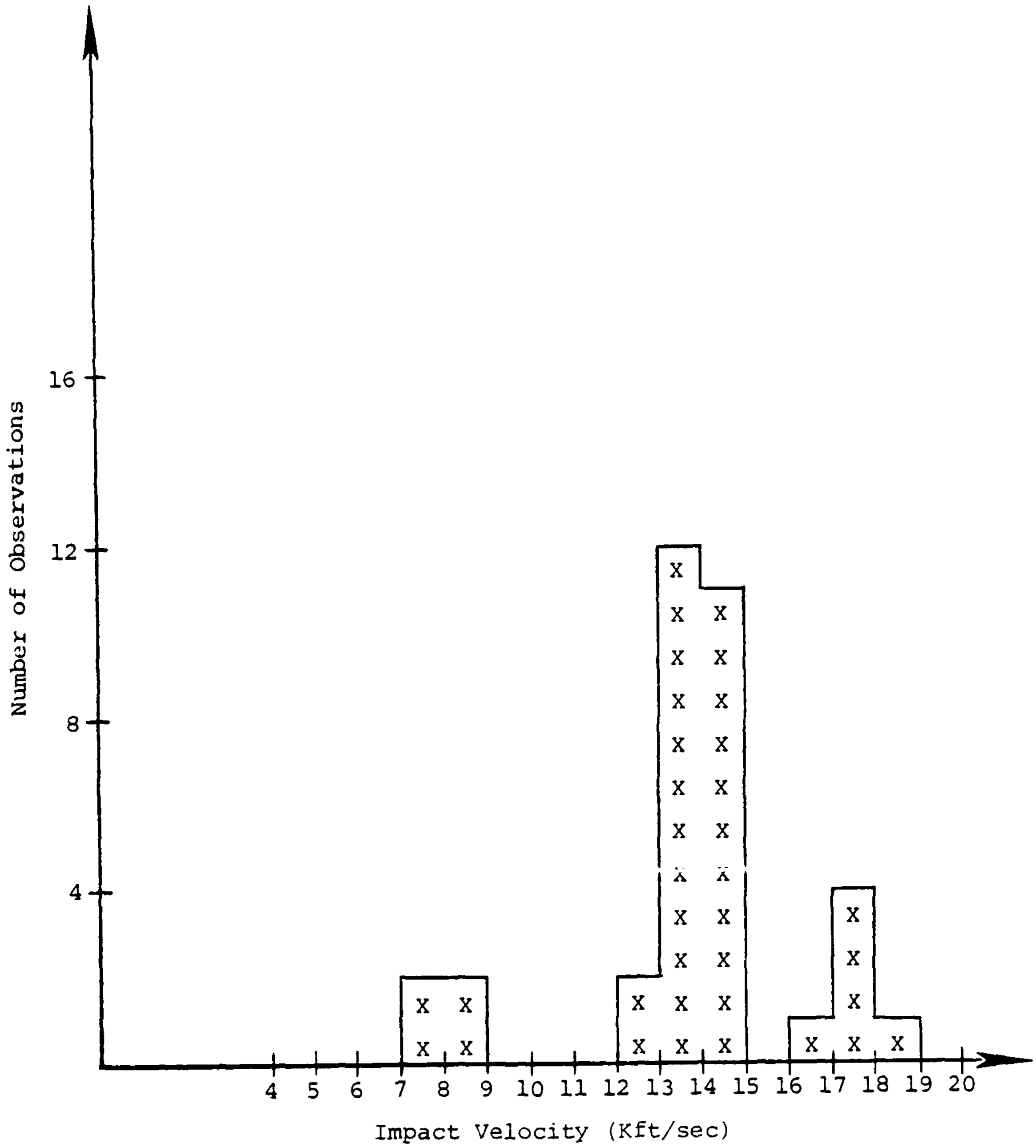


FIGURE 3.1: DISTRIBUTION OF IMPACT VELOCITIES FOR SERIES 300 CARBON-CARBON COMPOSITE (Temperature $\leq$ 70°)

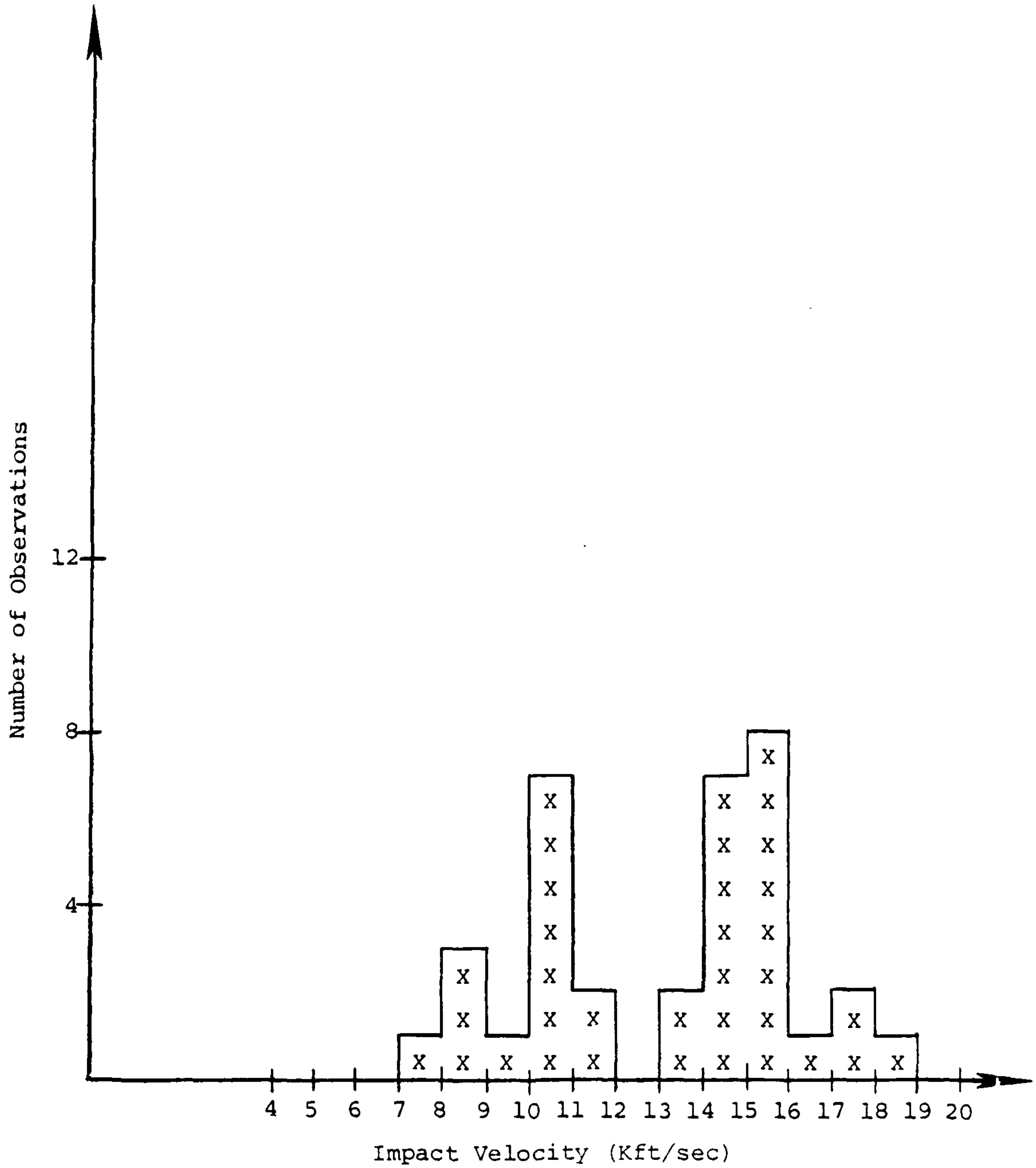


FIGURE 3.2: DISTRIBUTION OF IMPACT VELOCITIES FOR SERIES 400 CARBON-CARBON COMPOSITE (Temperature $\leq$ 70°)

4. ADAPTIVE LEARNING NETWORK MODELS

The dependent variables of interest are the gravametric (G_m) and volumetric (G_v) mass loss due to single-particle impacts. Other parameters, such as crater depth and radius, are reported for only a few observations. As a result, ALN models were created for G_m and G_v only. For similar reasons, models were created using only observations of impacts on State 1 (virgin) samples.

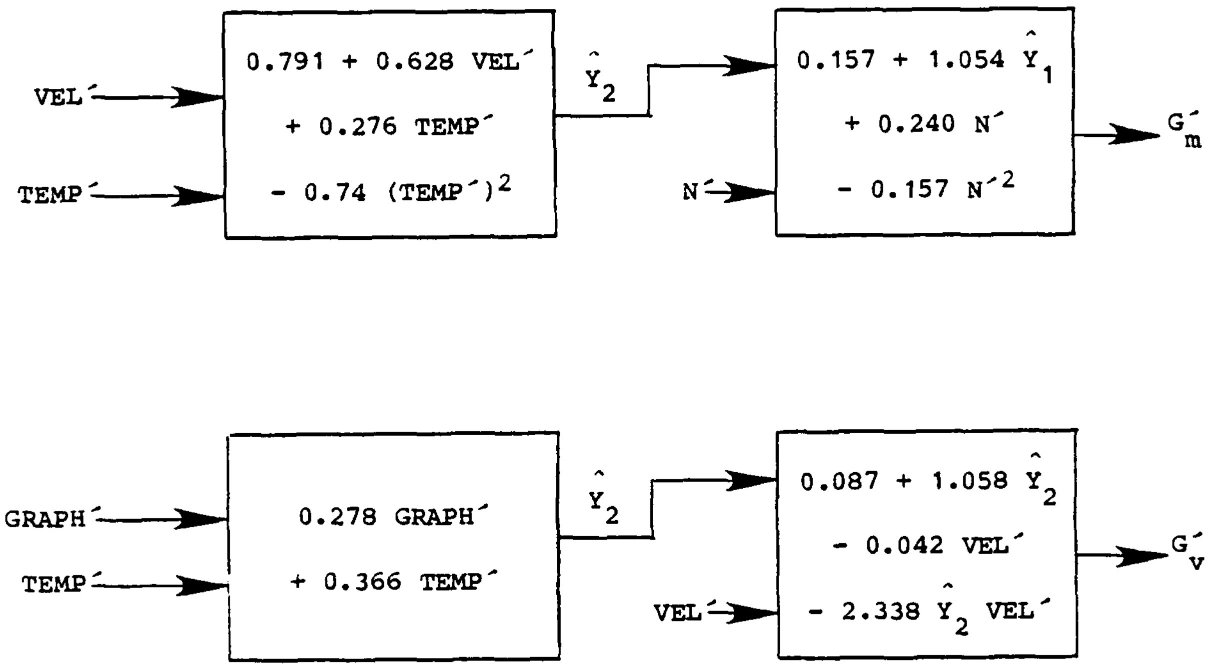
Candidate input variables for the ALN models are given in Table 4.1. Only those variables that were present for most observations in the data base were used. Observations for which one or more variable values were missing were not used in training the ALN models.

Figures 4.1 and 4.2 present the ALN models of G_m and G_v for the Series 300 and Series 400 material samples, respectively. The figures show the inputs selected by the models and the equations implemented by each element of the models. Also given are the scale factors required by the models. The figures show that impact velocity is an important variable, as are the material hardness coefficients, N and A. Of the manufacturing variables, the graphitization temperature and bulk density are important. Testing temperature is also selected for the Series 300 model.

"Shear" was missing for many of the Series 400 observations. Because "Shear" did not appear to be an important variable (it did not appear in the model), the Series 400 model was also trained on the larger number of observations

TABLE 4.1: INDEPENDENT VARIABLES FOR ALN MODELS

GRAPH
LASTGR
BULKDEN
A
N
SHEAR
VEL
TEMP



$$GRAPH' = (GRAPH - 2990.60)/158.69$$

$$N' = (N - .476)/.070$$

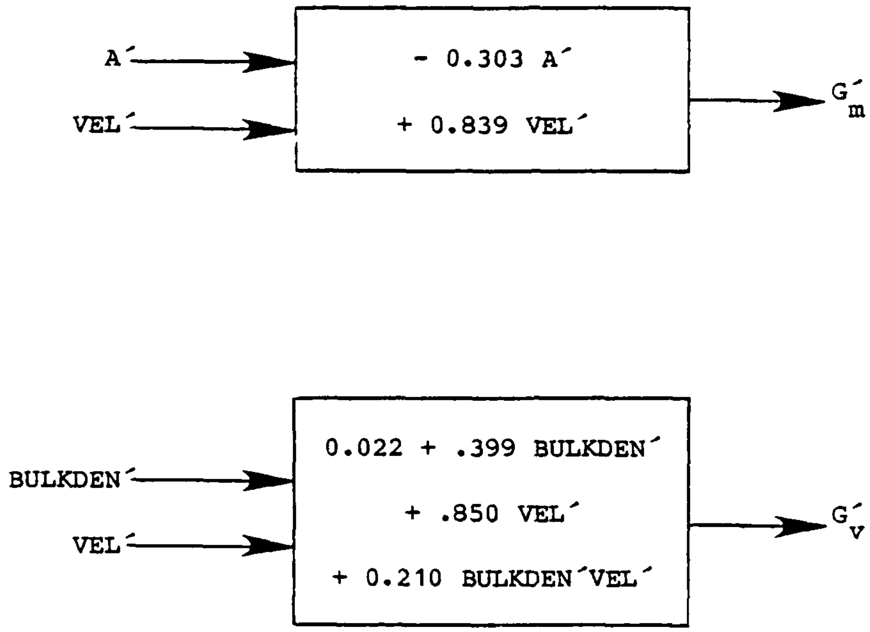
$$VEL' = (VEL - 13.82)/2.133$$

$$TEMP' = (TEMP - 2469.40)/2331.72$$

$$G_m = 7.27G'_m + 24.18$$

$$G_v = 5.58G'_v + 22.65$$

FIGURE 4.1: ALN MODELS OF G_m AND G_v FOR VIRGIN SERIES 300 MATERIAL SAMPLES



$$A' = (A - 456.31)/7315$$

$$BULKDEN' = (BULKDEN - 1.961)/0.019$$

$$VEL' = (VEL - 11.12)/5.96$$

$$G_m = 17.50\ G'_m + 25.43$$

$$G_v = 15.61\ G'_v + 23.25$$

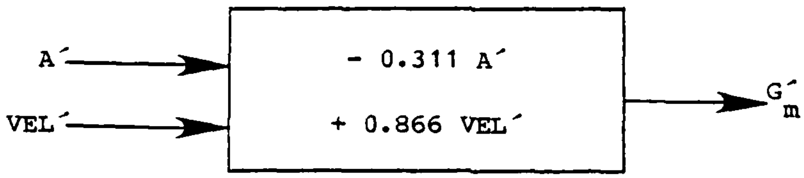
FIGURE 4.2: ALN MODELS OF G_m AND G_v FOR VIRGIN SERIES 400 SAMPLES; "Shear" Not Included as an Independent Variable

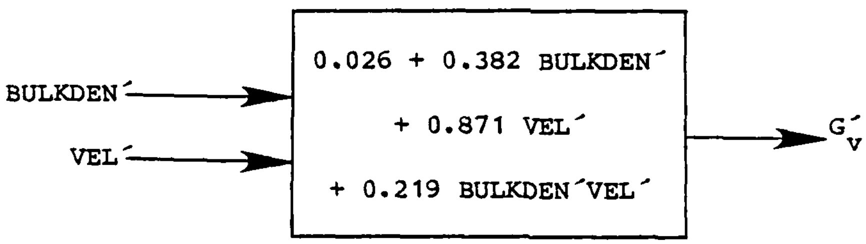
that became available by not using "Shear" as an input variable. The resulting model is shown in Figure 4.3. Comparison of Figures 4.2 and 4.3 indicates the similarity of the models. Thus, the model was not sensitive to the choice of observations making up the training data base.

Consideration of the physics of the impact process shows that the mass loss should be zero at zero impact velocity. It is possible to constrain the ALN models to this requirement by duplicating each observation in the data base, and substituting zeroes for the impact velocity and the mass loss ratios. Figure 4.4 shows the ALN models of G_m and G_v for the Series 300 materials when so constrained.

The mass loss should be dependent in the kinetic energy of the impacting particle, or approximately proportional to the square of the impact velocity. The ALN methodology permits the resulting models to have a power law dependence on any of the input variables. It is also possible that non-integral exponents are appropriate to the data; if so, the appropriate non-integral exponents will be discovered during ALN synthesis. For the available data base, all of the ALN models are linear in the impact velocity variable. As noted above, two velocity regimes are present in the data (three if zero velocity is included). Thus the variety of impact velocities in the data does not support higher order or non-integral dependence of the mass loss on the impact velocity. More complete data could be used to make such a determination.

Open porosity and CVD are thought to be important parameters governing the erosion resistance of materials. ALN models of G_m and G_v for the Series 300 and Series 400 data, including these qualities, are shown in Figures 4.5





$$A' = (A - 415.93)/37.11$$

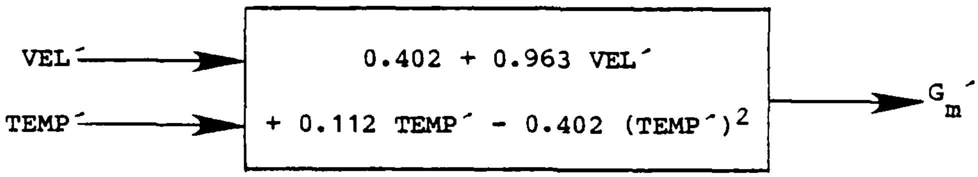
$$BULKDEN' = (BULKDEN - 1.964)/0.022$$

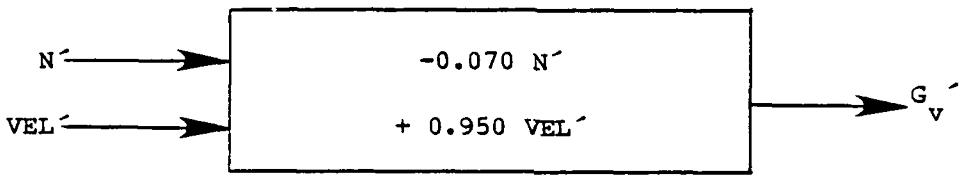
$$VEL' = (VEL - 11.09)/6.21$$

$$G_m = 18.73\ G'_m + 27.52$$

$$G_v = 16.87\ G'_v + 25.26$$

FIGURE 4.3: ALN MODELS OF G_m AND G_v FOR VIRGIN SERIES 400 SAMPLES; "Shear" Included as a Candidate Independent Variable





$$N' = (N - 0.477)/0.073$$

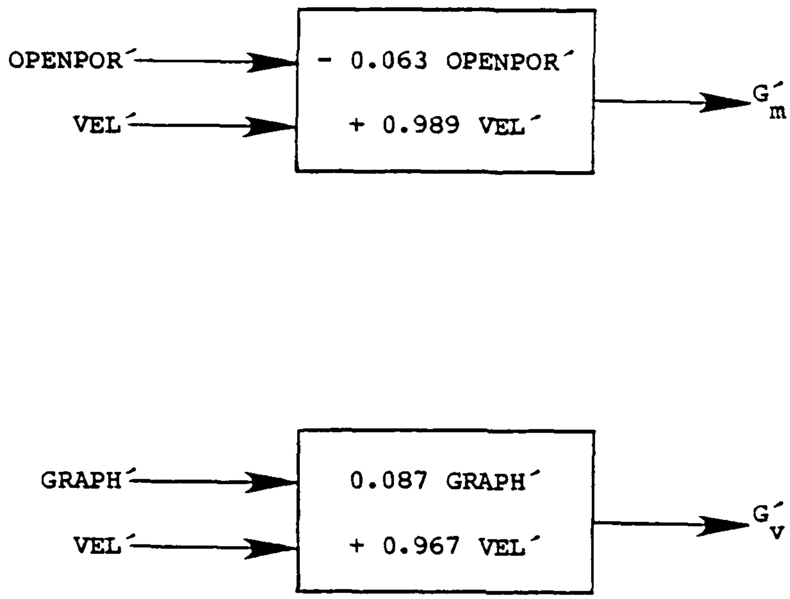
$$VEL' = (VEL - 11.025)/5.870$$

$$TEMP' = (TEMP - 2490.71)/2245.62$$

$$G_m = 11.69\ G_m' + 19.29$$

$$G_v = 10.38\ G_v' + 18.07$$

FIGURE 4.4: ALN MODELS OF G_m AND G_v FOR VIRGIN SERIES 300 MATERIAL; CONSTRAINED TO ZERO MASS LOSS AT ZERO IMPACT VELOCITY



$$GRAPH' = (GRAPH - 2541.07)/174.77$$

$$OPENPOR' = (OPENPOR - 5.79)/1.44$$

$$VEL' = (VEL - 9.55)/6.58$$

$$G_m = 14.54\ G'_m + 20.84$$

$$G_v = 10.62\ G'_v + 15.11$$

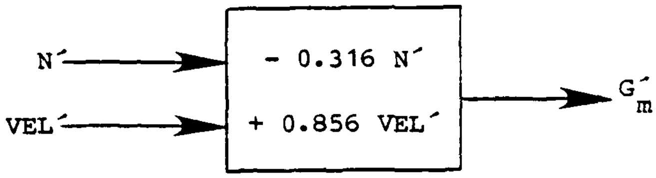
FIGURE 4.5: ALN MODELS OF G_m AND G_v FOR VIRGIN SERIES 300 SAMPLES; "CVD" and "Openpor" Used as Candidate Input Variables

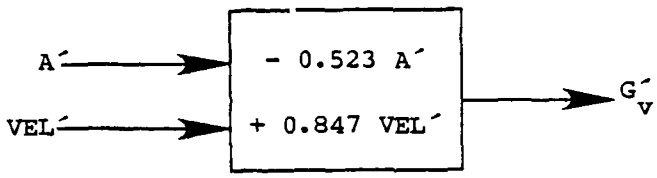
and 4.6. Here, both open porosity and the graphitization temperature are selected. It is tempting to suggest that this indicates the importance of open porosity and graphitization temperature. Unfortunately, only 28 data observations were used in arriving at the model. Additionally, all samples that include open porosity and CVD as variables were tested at 4000°. A similar set of models for the Series 400 data (based on 19 observations) does not select open porosity and CVD, and is quite similar to the other models (Figure 4.6).

The above discussion pertains to a number of different empirical ALN models of G_m and G_v for both Series 300 and Series 400 material samples. As noted, the data base is limited in terms of variety and is replete with many missing values. Nonetheless, the ALN models do show important features of the usable data observations. Primary among the conclusions that can be drawn is that the impact velocity is the most important variable in the data base. In all cases, the models are linear in velocity. The data do not support higher-order dependence on velocity, either quadratic or fractional.

Secondarily, the material properties N, A, and bulk density appear often in the models. There are indications that open porosity may be an important variable, but the models that include this parameter are based on very little data.

Of the manufacturing variables, graphitization temperature and the last graphitization temperature appear.





$$N' = (N - 0.525)/0.037$$

$$A' = (A - 394.05)/12.52$$

$$VEL' = (VEL - 11.34)/5.88$$

$$G_m = 19.97\ G'_m + 32.32$$

$$G_v = 16.50\ G'_v + 23.82$$

FIGURE 4.6: MODELS OF G_m AND G_v FOR VIRGIN SERIES 400 SAMPLES; "CVD" and "Openpor" Used as Candidate Input Variables

The fact that the testing temperature appears in the ALN models may be indicative of the difficulty in experimentally separating ablation mass loss from impact mass loss at the higher temperatures.

5. CONCLUSIONS AND RECOMMENDATIONS

The goal of this study was to investigate the feasibility of a unified model of erosion of materials exposed to impact of single particles at velocities to and including hypersonic. From the results presented in Section 4 it is apparent that the development of an erosion model is quite feasible. Unfortunately, the data which were available for this project had some inherent limitations which precluded more definitive results. Specifically, the ranges of many of the variables included in the data base were quite limited, and in some cases the values of variables were constant for many or all experiments. As has been mentioned in previous sections, the presence of missing parameter values decreased the number of usable experiments.

In spite of the above data limitations and resulting modeling difficulties, the ALN modeling procedure identifies N, A, bulk density, and graphitization temperatures as the most important of those variables that can be controlled.

This work has shown that ALN models of specific quantities (G_m and G_v) may be developed from limited experimental data. The next logical step in the practical use of the Adaptive Learning Network method is to use it in ongoing experimental programs. It is recommended that new data be subjected to ALN analyses as such data become available. The resulting models can be examined to determine optimum manufacturing processes and subsequent material testing to verify and further refine the models.

APPENDIX

LITERATURE REVIEW

The completion of much of the work reported in this document demonstrated that the overall lack of data and lack of variability in many variables in the available data base limited the utility of the work performed. A literature survey was undertaken with the specific goal of locating additional Series 300 and Series 400 data that might be added to the current data base.

The following documents were reviewed:

Brown, Joseph, "Erosion Performance of Carbon Composite Materials", Final Report for Contract No. N60921-79-C-0127, March 1980.

This report describes a theoretical study of the erosion properties of nosetip component materials using the MACE computer program. Experimental data are not presented.

Brown, Joseph, J. Cresswell, and N. Diaz, "Erosion Analysis of Heatshield Materials and Concepts", Technical Report for Contract No. AFWAL-TR-80-4113, September 1980.

The work discussed in this report used the MACE computer code to study advanced concepts for heatshield material; no experimental data are presented.

Carlyle, John D., "Comparison of Polyarylonitrile (PAN) and Thornel-50 (T-50) Nosetip Material (U)", Report No. SAMSO-TR-77-90, May 1977 (C).

The report compares single-particle impact tests on T-50 and PAN materials with GE223. The GE223 data are from ETI-75-1929, CR-75-329, cited previously.

Graham, Marlyn E., "GE223 Carbon-Carbon Single Particle Impact Data Summary (U)", Report No. ETI-75-1929, CR-75-329, December 1975 (S).

This report contains data on GE223 carbon-carbon billets 317, 318, 319, 320, 331, 334, 335, 337, and 343. Mass loss and material properties of the billets are given, but not the manufacturing variables.

Graham, Marlyn E., and J.D. Carlyle, "Erosion Materials Final Report, Vol. 1, Hypervelocity Particle Impact Response of ATJS Graphite and a Comparison with GE223 Carbon-Carbon Response (U)," Report No. SAMSO-TR-76-226, July 1977 (C).

Data presented in this report summarize single-particle impact tests performed on ATJS graphite by ETI. Mass losses are given as a function of specimen and impacting particle properties. The data do not include manufacturing variables.

McHenry, Michael R., "Design Technology Program, Vol. II, Erosion Model for Hypervelocity Impacts (U)," Report No. ETI-78-2668, CR73-564, October 1978 (C).

This report describes a model for calculating mass loss ratios and crater dimensions for single-particle impacts. New data are not reported.

McHenry, Michael R., "Particle Impact and Dynamic Response of Advanced Nosetip and Heatshield Materials (U)," Report No. AFML-TR-78-2040, February 1979, (C).

This report contains small amounts of data representative of a variety of different materials. No data of use in the current program were found.

McHenry, Michael R., and M.E. Graham, "Design Technology-E Program, Vol. III, Erosion Testing Results, 1978 (U)," Report No. CR78-562, SAMSO-TR-79-82, December 1978 (C).

Hypervelocity impact tests are described for a number of nosetip materials. Data useful in the current program are not included.

Phinney, Ralph E., and R.A. Leverance, "Single Particle Impact on ATJ-S Graphite", Report No. NSWC,WOL/TR-75-199, December 1975.

This report contains a tabulation of data of impact of various particles on graphitic material. Data include determination of crater depth and volume as functions of impacting particle type and velocity. Analysis of the data in terms of a simple theoretical model shows that the crater depth was strongly correlated with the kinetic energy of the compacting particle.

Review of these documents did not identify any data that could be added to the data base for the present project. One document did provide partial data on several Series 300 billets. Consultation with cognizant Government personnel revealed that most of the available data had been supplied to Adaptronics.*

* Adaptronics Project Review held at AFWAL, 25 June 1980.

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3. The Kolmogorov-Gabor Polynomial is a special case of the generalized nonanalytic, nonlinear, autoregressive-moving average process model. See also: Cook, F.J. and J.N. Craig, "Adaptive Learning Networks and Image Processing for Missile Guidance," Proceedings of the Society of Photo-Optical Instrumentation Engineers, Vol. 238, Image Processing for Missile Guidance, August, 1980.

4. Gilstrap, L.O., Jr., "Keys to Developing Machines with High-Level Artificial Intelligence," Proc. ASME Design Eng. Conf., (1971), pp. 1-16.

5. This technique is used by Adaptronics, Inc. Polynomial Network Training Routine, Version II: PNETTR II, 1976.

6. Mucciardi, A.N. and E.E. Gose, "An Automatic Clustering Algorithm and Its Properties in High-Dimensional Spaces," IEEE TRANS. SYST. MAN AND CYBERN., 1971, pp. 247-254. See also CLUSTR II in Adaptronics Proprietary Software Library.

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8. Maklad, M., "On Model Building from Operating Records," doctoral dissertation, Dept. of Elect. Eng., Univ. of Calgary, April 1978.

9. Adaptronics, Inc., Polynomial Network Training Routine, Version IV: PNETTR IV, 1980.